

Hurricane Landfall Predictions

Group 2

Charles Ho, Anna Peris, Lee Richardson
SAMSI Undergraduate Modeling Workshop

Outline

- Introduction
- Methodology
- Proposed model
- Prediction of landfalls

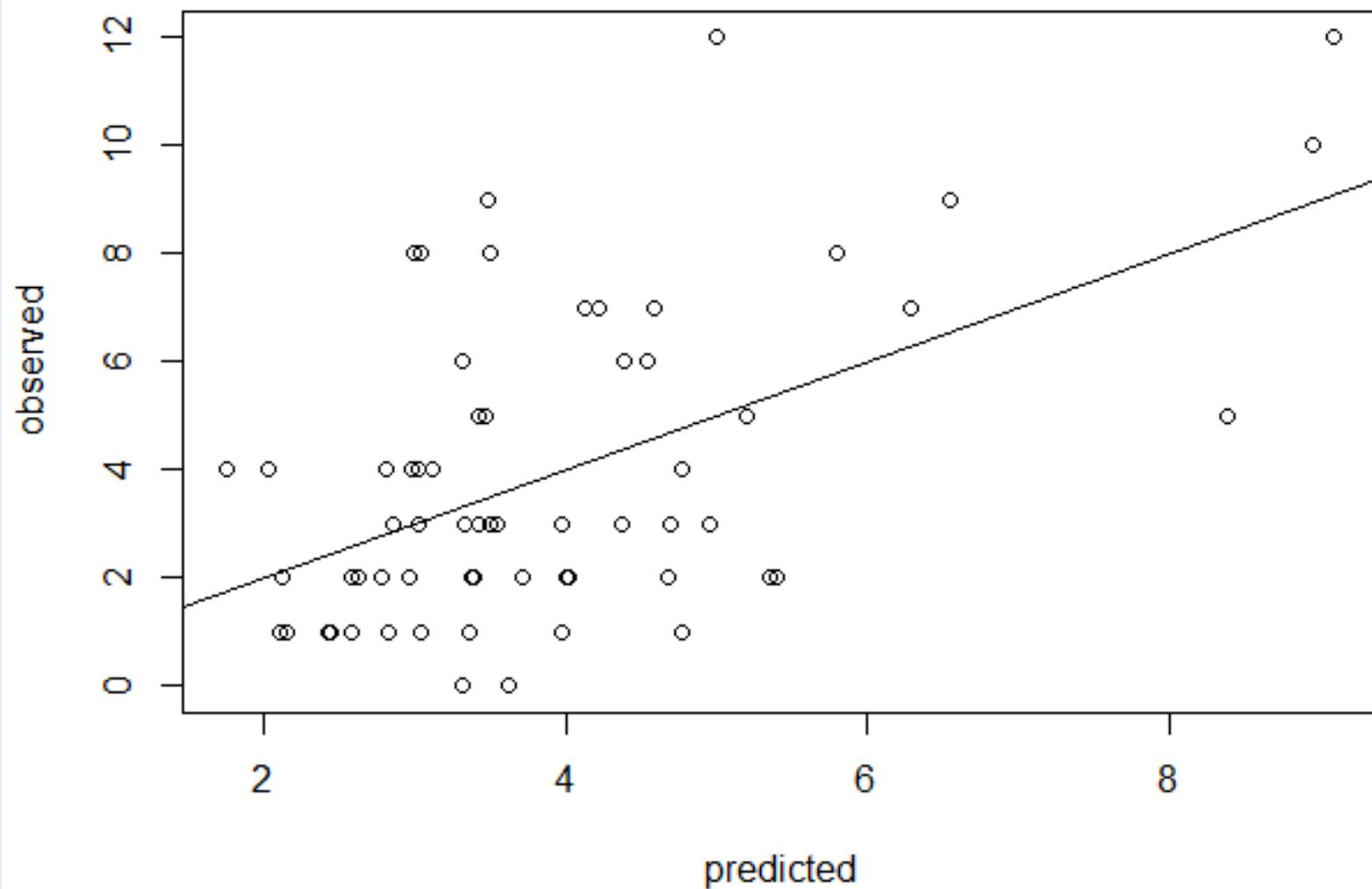
Introduction

- Initially, already had predicted number of tropical cyclones
- Wanted to predict number of cyclones that make **landfall** in the U.S
- Identified covariates from data set which best predict future landfalls.

Yearly average of covariates

- Computed yearly means of each covariate from original dataset
- Used step AIC (Poisson) to select the most predictive covariates
- Landfall Hurricanes = amo + ao + limcar + mdrsst_necp + nao + qbo + tna + whwp
- R = .543

Predicted vs. Observed models with Original Plot

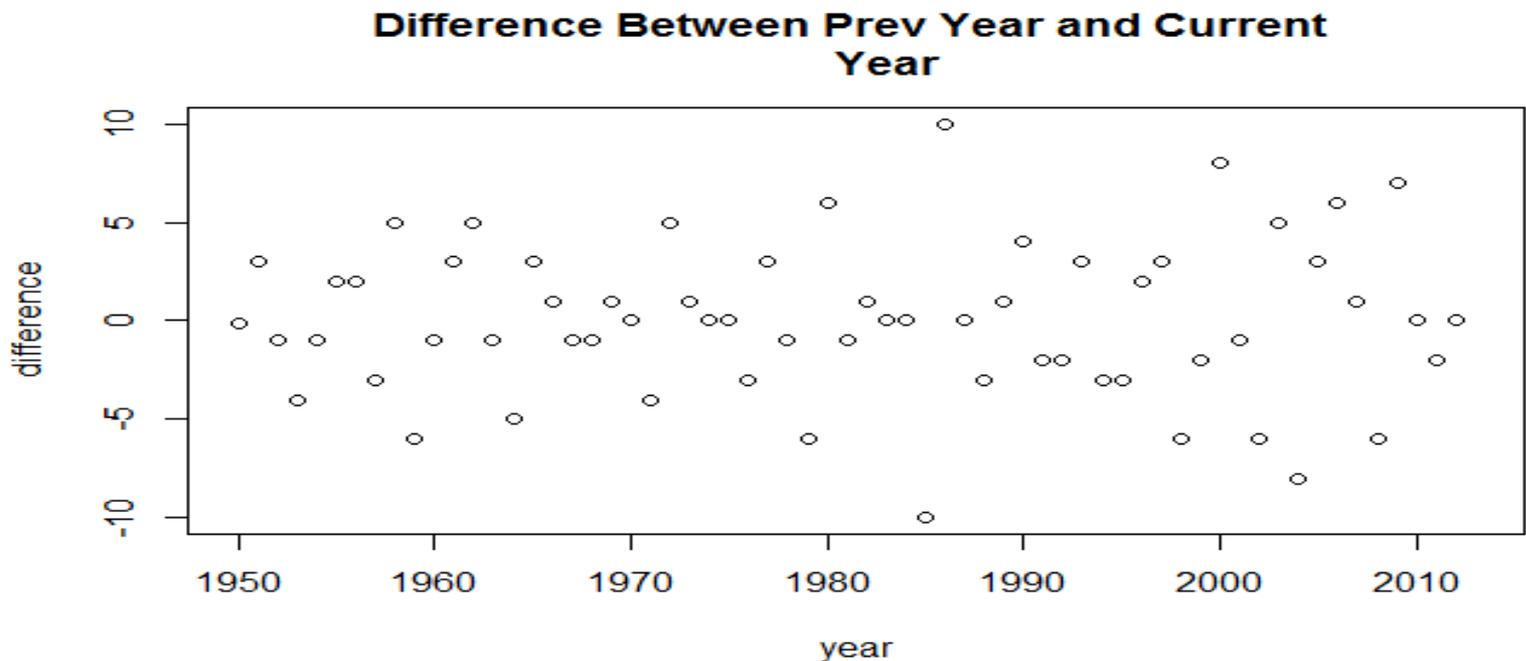


Previous year's landfall count

- There may be dependence between yearly hurricane counts
- Previous year's landfall count affects the subsequent year's count
- Created new variable which reflects the number of hurricanes that made landfall in the previous year

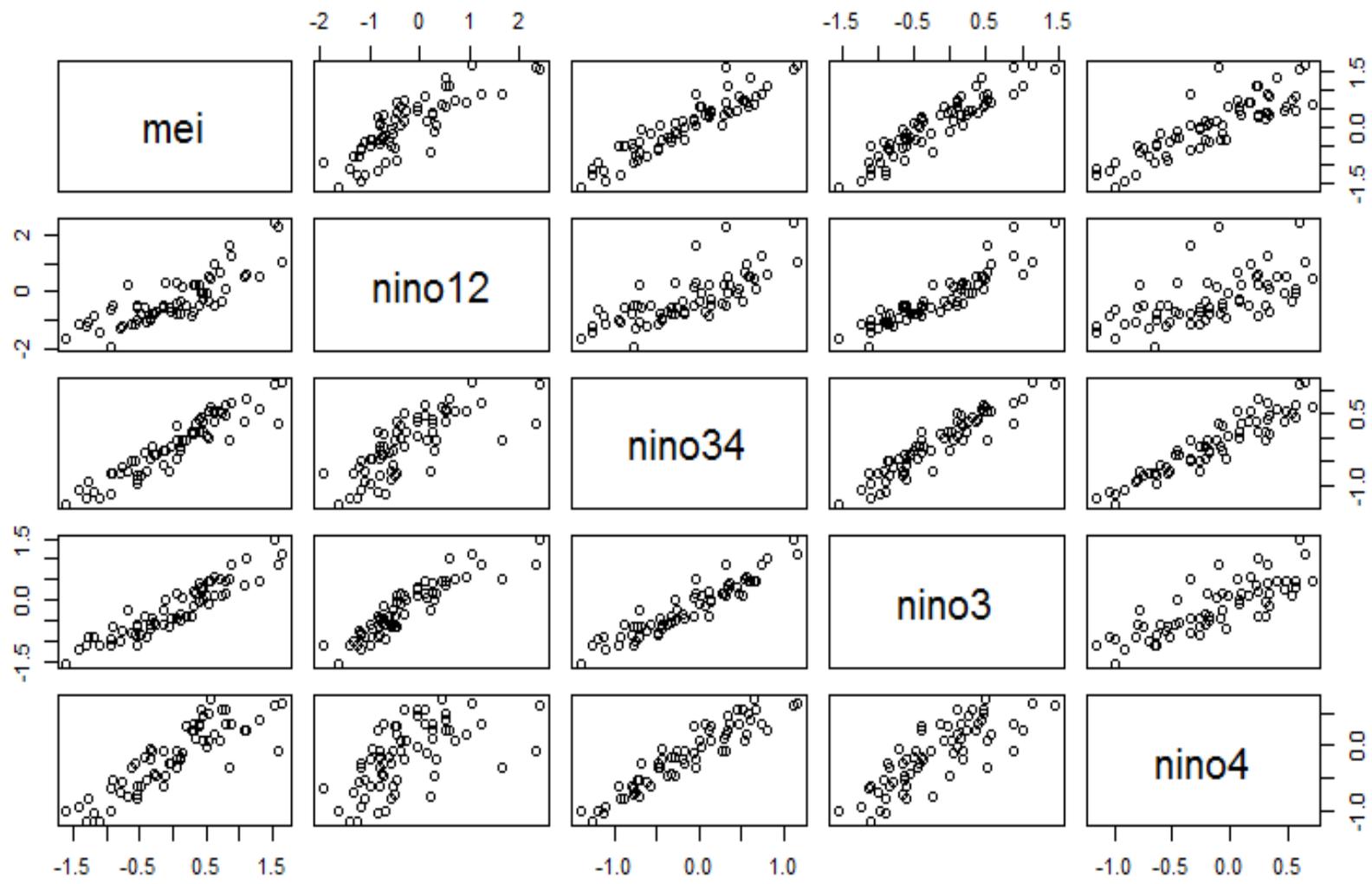
Previous year's landfall count

- Ran step AIC with this new variable
 - This new variable was not selected as an important covariate



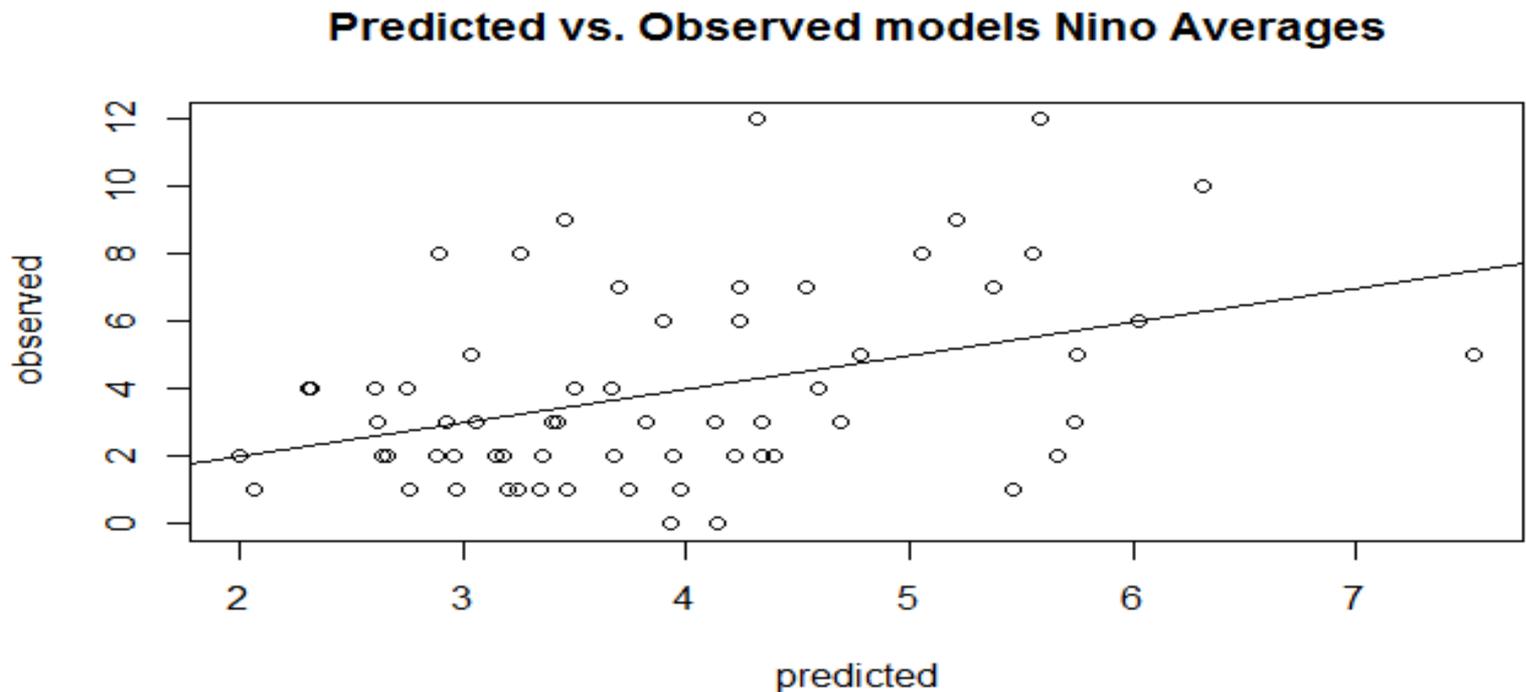
“El Nino” Model

- Hurricanes = amo + nino12 + nino34 + nino3 + sgst + whwp + r6mh
- 3 El Nino covariates in this model



Nino Average AIC Results

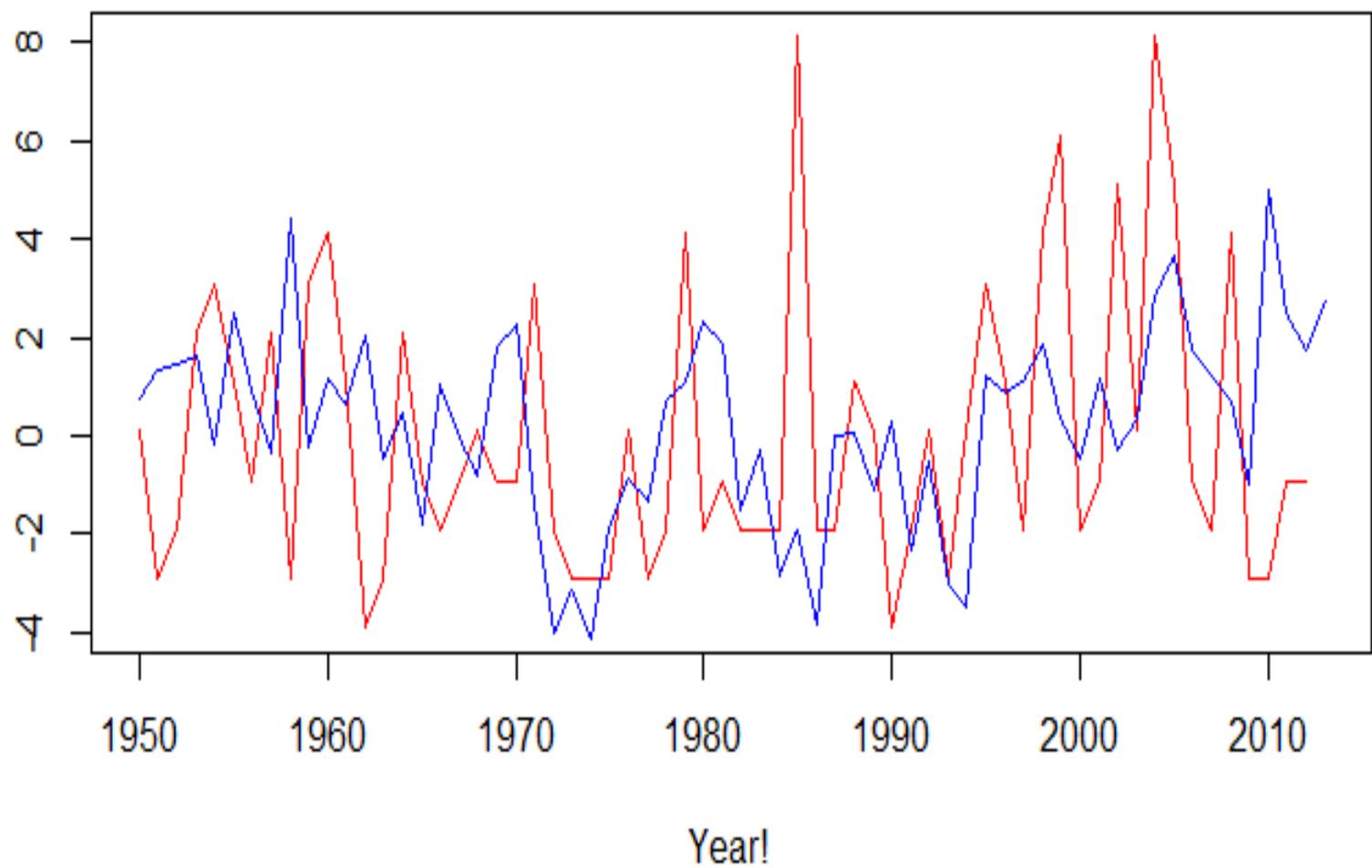
- Hurricane = amo + qbo + whwp
- $R = .402$



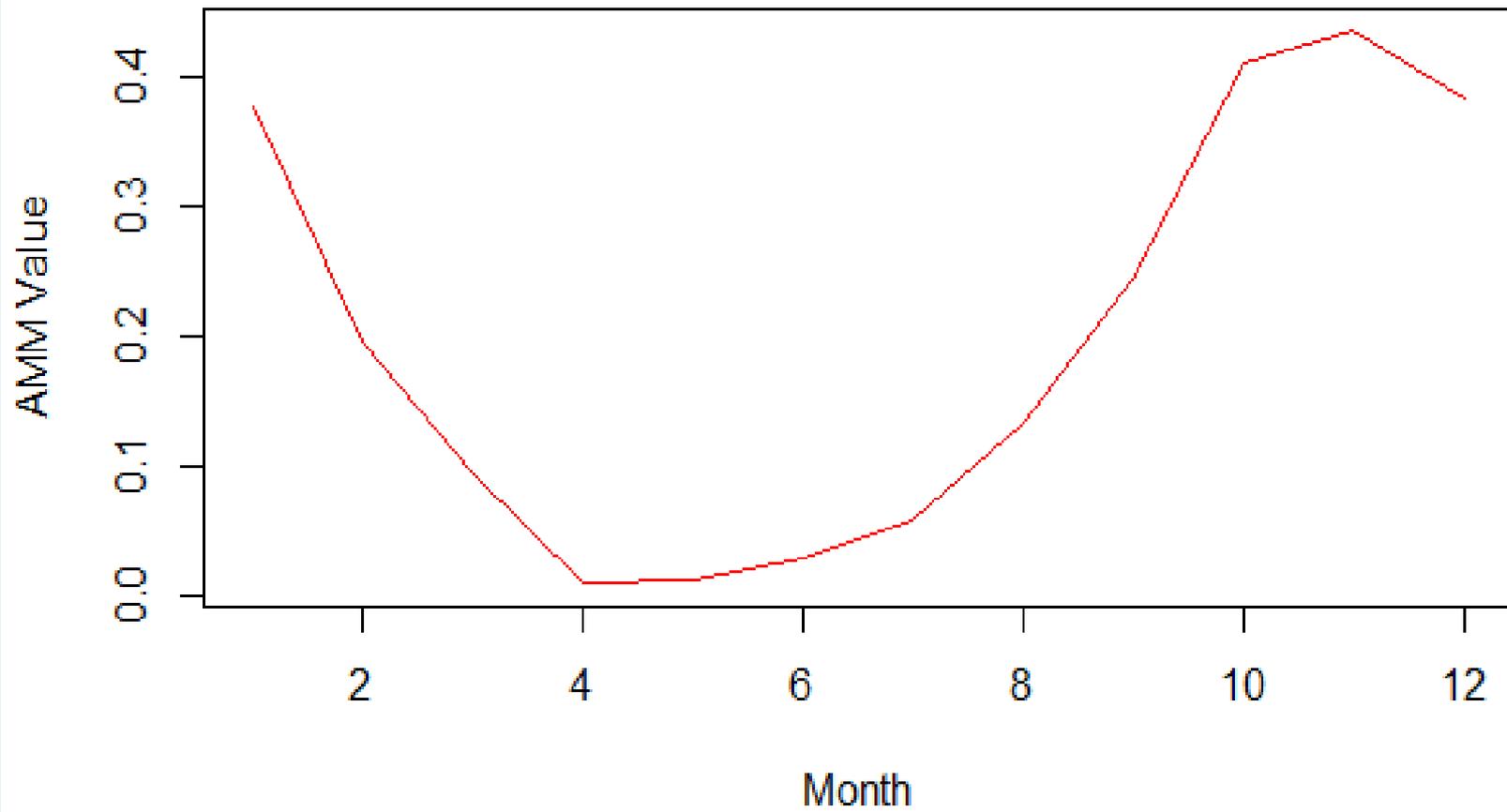
Landfall count anomalies

- Investigated landfall count anomalies
 - The difference between actual number of landfalls per year and the average number of landfalls over the entire time period
- Sought covariates which were associated with extreme anomalies
 - Compared trends between landfall counts and individual covariates
 - 1985, 1999, and 2004 : busy seasons

Amm Vs Hurricane Anamolies



AMM By Month

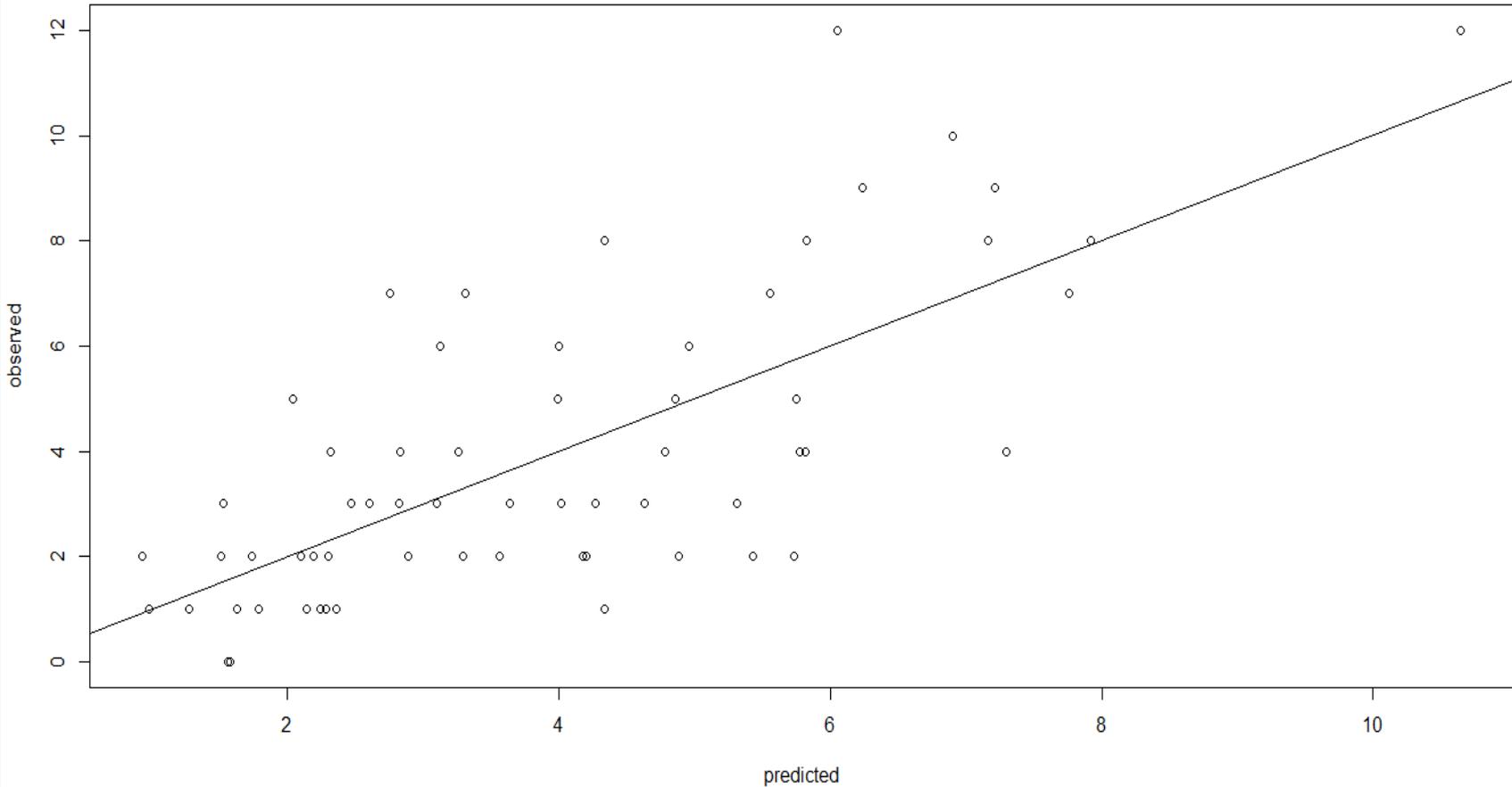


Quarterly examination of data

- Covariates may have varying predictive ability depending on the time of year
- Investigated the dataset by 3-month chunks using step AIC to select best covariates
 - Generated 3 models
 - January to March
 - April to June
 - July to September
 - October to December

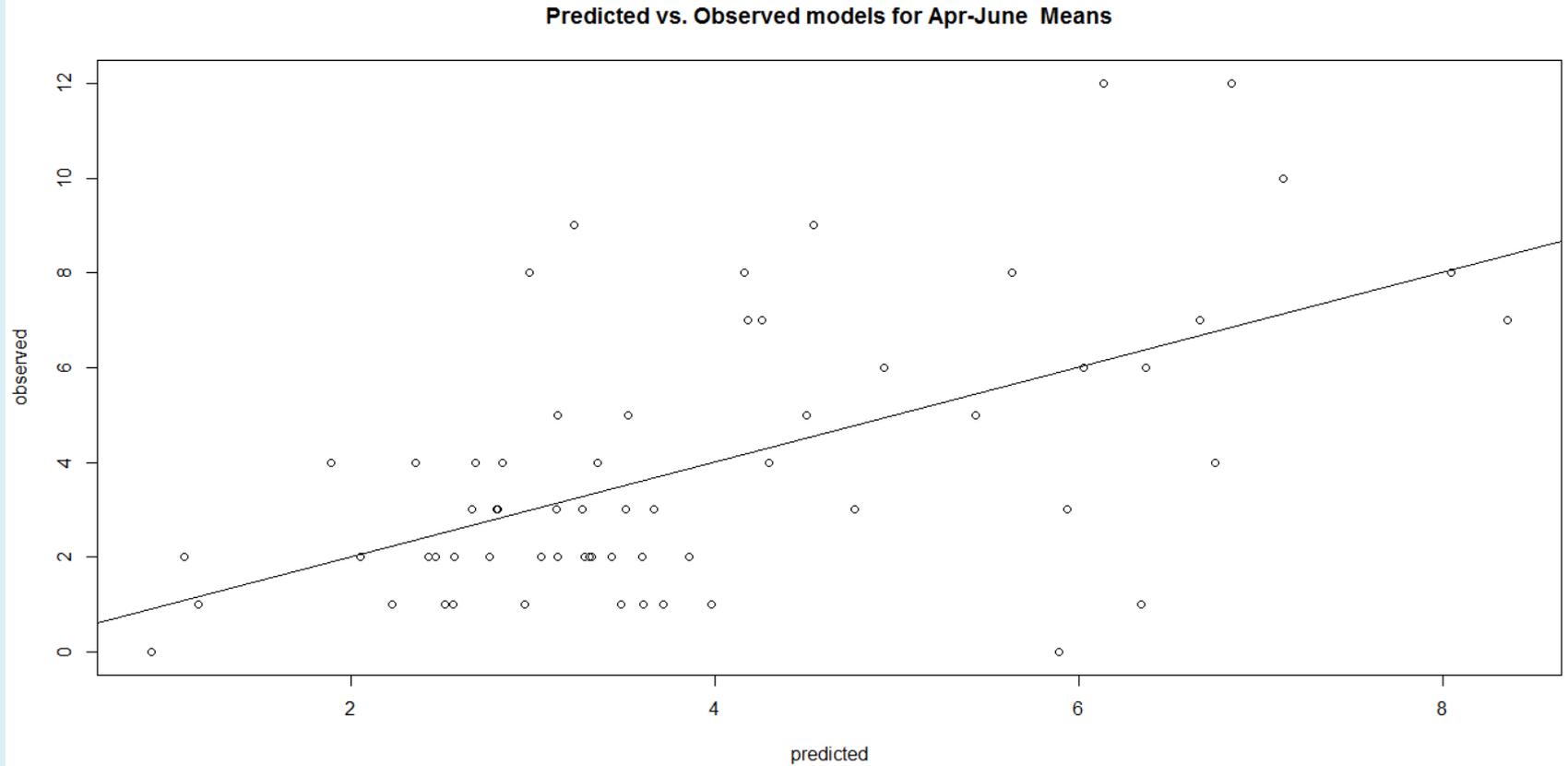
1st Quarter

Predicted vs. Observed models for Jan, Feb, and March Means



- $R = .7248064$

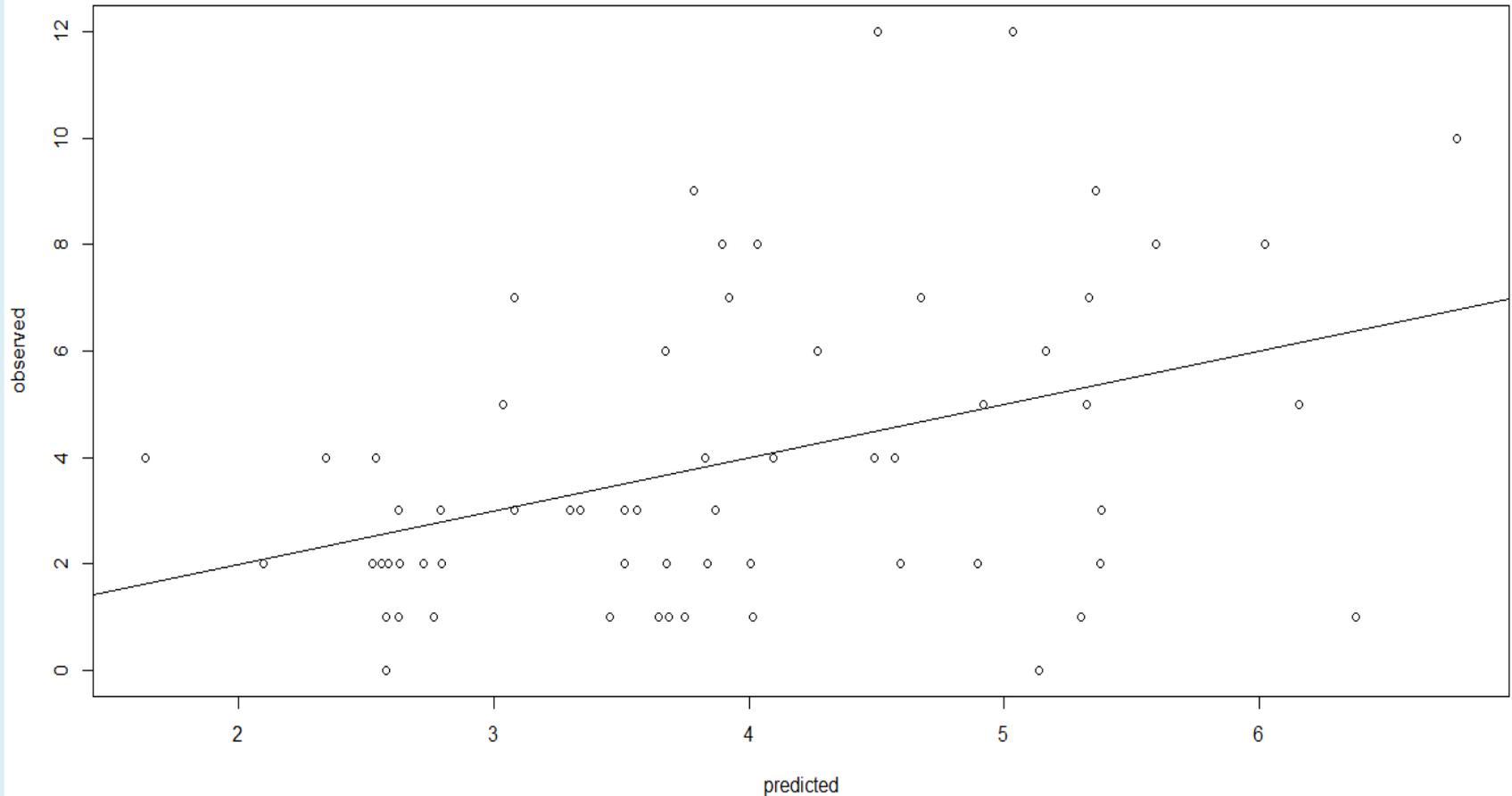
2nd Quarter



R = .5771428

3rd Quarter

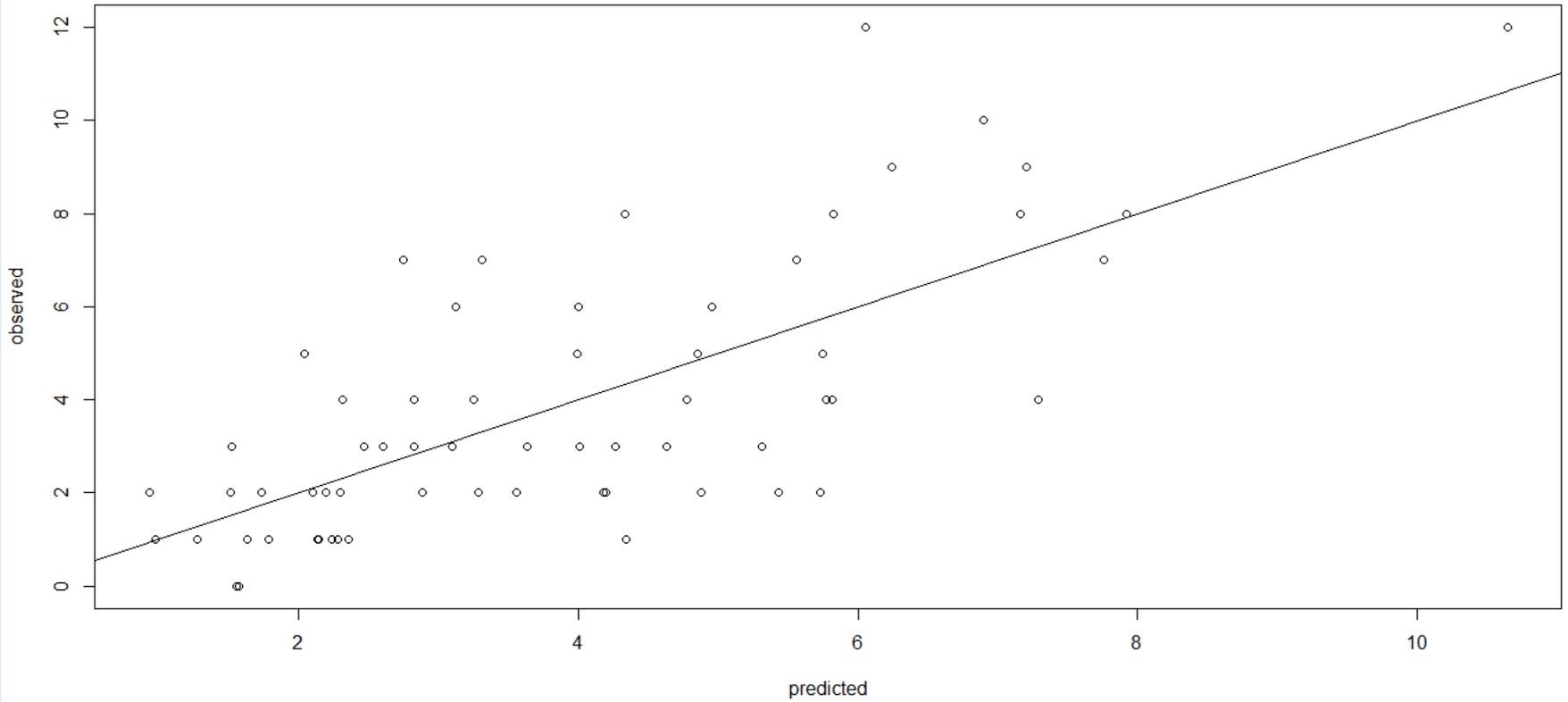
Predicted vs. Observed models for July-Sept Means



R = .4089

4th Quarter

Predicted vs. Observed models for Oct-Dec Means



$R = .777$

Cross Validation

Cross-validation was used to select the best of the proposed models

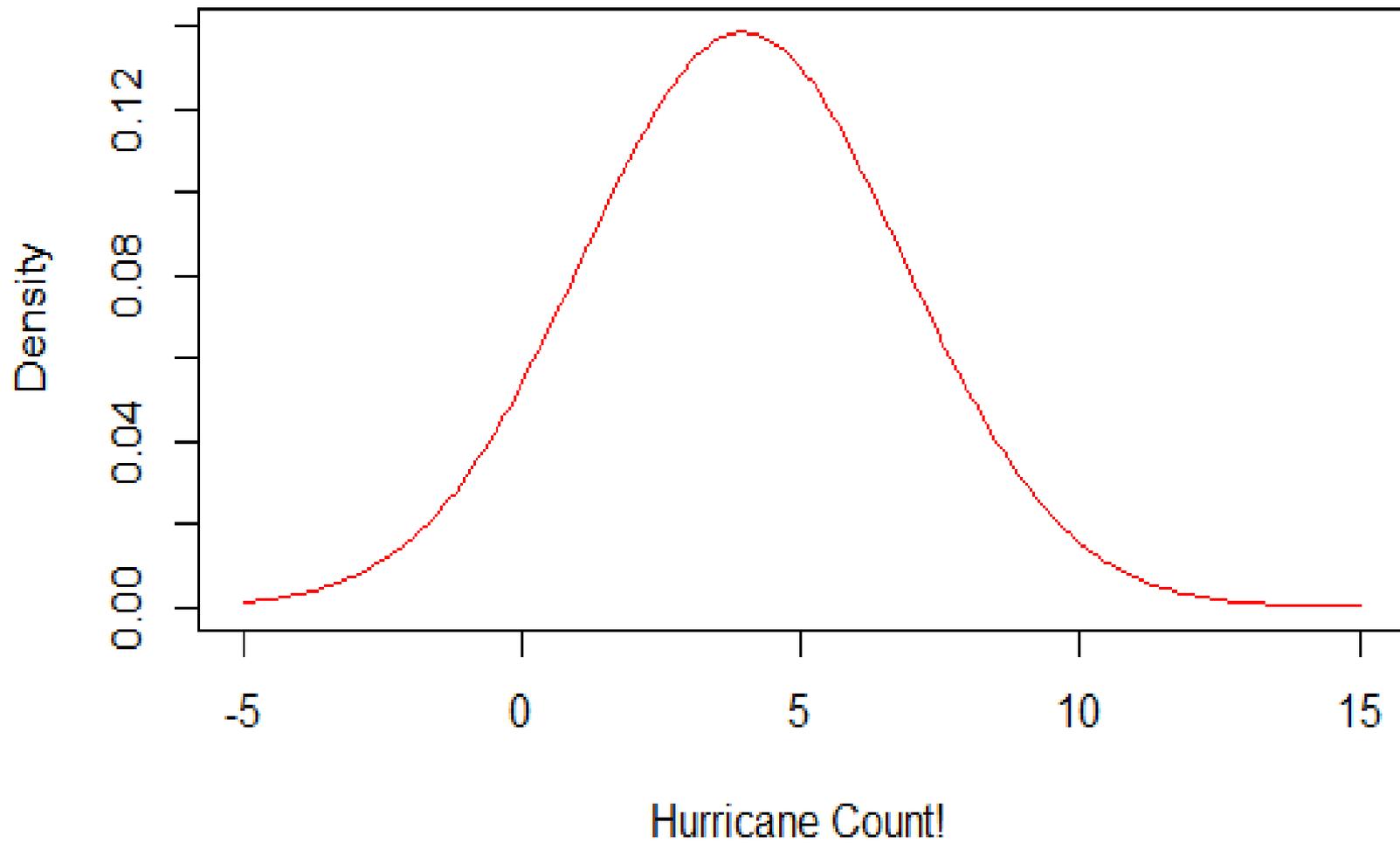
Model	CV Output
Yearly Average	4.218075
Quarter 1	4.638036
Quarter 2	4.430353
Quarter 3	4.665247
Quarter 4	4.273530

Model Selection

- Hurricanes = amo + nin.avg + limhaw + limind + mdrslp + limind + sri
- R = .725
- Mean Predicted Hurricanes: 3.96
- Standard Deviation Hurricane Count: 2.88

Hurricane Count	0	1	2	3	4+
Probability	.074	.107	.135	.151	.549

Hurricane Count Distribution



Thoughts for Future Investigations

- Manipulate dataset so that data followed the course of the hurricane season (i.e. each hurricane season should begin with December of the previous calendar year)
- Investigate if selected covariates are highly dependent on human effects
- See if man made climate change is causing an increase in earthquakes
- Look at the predictions for total hurricanes and see what percentage of them reach land.
- Use different region Previous year counts.
- Compare physical theories with data collected (Warm Water, Rainfall, Shear)
- Regression techniques (weighting, interactions, smoothing, etc.)
- Look at patterns in data during specific formations of hurricanes
- Observe without extreme years,

Conclusion

- Very Large, complex problem with lots of variables and analysis to consider, and future data to be collected
- Is man-made global warming increasing the amount of hurricanes per year?
- Signal in the Noise?